

WAVELET POWER SPECTRUM-BASED PREDICTION OF SUCCESSFUL DEFIBRILLATION FROM VENTRICULAR FIBRILLATION

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Abstract – This paper reports on work in progress to develop a wavelet-based method of outcome prediction after DC countershock. The method correlates return of spontaneous circulation (ROSC) with features of the wavelet-based power spectra derived from the ECG during ventricular fibrillation.

Keywords - Ventricular fibrillation, wavelet transform, defibrillation, shock outcome prediction, Cardiac arrest, resuscitation, advanced life support.

I. INTRODUCTION

Ventricular fibrillation (VF) is the most common cause of sudden cardiac death [1,2]. Considerable interest has focused upon this condition as it is recognised that prompt electrical cardioversion can be life saving, though the efficacy of this treatment declines rapidly if the patient remains in VF for more than a few minutes. There has been considerable interest in analysis of the VF waveform in the search for pathophysiological clues, and ways to improve resuscitation success rates. Until recently, the surface electrocardiogram recorded during ventricular fibrillation (VF) was thought to represent disorganised and unstructured electrical activity of the heart—in stark contrast to the information rich ECG in other states of health and disease [3,4]. Recent work by the authors [5-7] has found that, in fact, by using continuous wavelet transform analysis a rich structure can be found in many cases of VF. This takes the form of both high frequency spiking and low frequency modulation of the high energy region in wavelet space. This paper details current work by our group to develop a method which will predict the return of spontaneous circulation (ROSC) subsequent to DC countershock based on wavelet-power spectral analysis of the VF waveform immediately prior to shock delivery.

II. METHODOLOGY

A. The Wavelet Transform

The wavelet transform is a valuable signal analysis tool that can elucidate spectral and temporal information from complex signals, including ECGs. It overcomes some of the limitations of the more widely used Fourier transform, which only contains globally averaged information, and has the potential to lose specific features within the signal. Recently, wavelet analysis has been applied to biomedical data including electroencephalogram, electromyogram, acoustic signals and the ECG [8-12]. Wavelet based studies of ECG signals have either examined heart rate variability, classified ECG waveforms, or have been used for ECG data

compression. Our group has focussed on the analysis of complex waveforms during ventricular fibrillation (VF) [5-7] (as well as other medical and engineering signals [13-15]).

The complete analysis of a signal requires the deduction of both the frequency make up and temporal location of the signal components. As a result of the infinite extent of the Fourier integral, analysis is time averaged. This renders feature location complex, even for stationary signals. This limitation can be partly overcome by introducing a sliding time window which localises the analysis in time. This local or Short Time Fourier Transform (STFT) provides a degree of temporal resolution by highlighting changes in spectral response with respect to time. However, this method is always a compromise between temporal and frequency resolution (higher frequency resolution means lower temporal resolution, and vice versa). The nature of the wavelet transform is such that it is well suited to analysis of signals in which a more precise time resolution is required for higher frequencies than for lower ones; i.e. the wavelet transform is suitable for locating discontinuities or singularities, in which high frequency components dominate. It effectively zooms in on the temporal signal when analysing higher frequencies, providing higher resolution where necessary.

The wavelet transform of a continuous real-valued time signal, $x(t)$, with respect to the real valued wavelet function, ψ , is defined as

$$T(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi^* \left(\frac{t-b}{a} \right) x(t) dt \quad (1)$$

where $\psi^*((t-b)/a)$ is the complex conjugate of the analysing wavelet used in the convolution and, in this application, $x(t)$ is the ECG signal exhibiting VF. The wavelet transform can therefore be thought of as the cross-correlation of the analysed signal with a wavelet function that has been translated by a value b and dilated by a factor a . These values are often referred to as the location and dilation parameters respectively.

Contemporary literature suggests two methods of wavelet analysis using either *discrete* or *continuous* transforms. The *discrete* wavelet transform necessitates the use of orthonormal wavelets, and dilation levels are set in the form of ‘octaves’ (integer powers of two). This provides a rapid method of signal decomposition, and guarantees energy conservation and exact signal reconstruction. However, the

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discrete transform is limited by loss of frequency resolution due to the incremental doubling of the level associated frequencies. Conversely, the *continuous* wavelet transform does provide high resolution. Thus, proper use of wavelet analysis demands identification of the correct wavelet and transform type for the given application. Our group have recently employed two types of wavelets for ECG signal analysis: the 2nd derivative of a Gaussian function and the Morlet wavelet. The former has temporal compactness, useful for examining location specific features in the signal. The latter is more compact in the frequency domain and allows both amplitude and phase of the signal features to be probed simultaneously.

The total energy contained in the signal, $x(t)$, is defined as its integrated squared magnitude

$$E = \int_{-\infty}^{\infty} |x(t)|^2 dt = \|x(t)\|^2 \quad (2)$$

The wavelet energy density plot – the scalogram – can be integrated across a and b to recover the total energy in the signal using the admissibility constant, C_g , as follows

$$E = \frac{1}{C_g} \int_{-\infty}^{\infty} \int_0^{\infty} |T(a, b)|^2 \frac{da}{a^2} db \quad (3)$$

The relative contribution to the total energy contained within the signal at a specific a scale is given by the scale dependent energy distribution:

$$E(a) = \frac{1}{C_g} \int_{-\infty}^{\infty} |T(a, b)|^2 db \quad (4)$$

Peaks in $E(a)$ highlight the dominant energetic scales within the signal. We may convert the scale dependent wavelet energy spectrum of the signal, $E(a)$, to a frequency dependent wavelet energy spectrum $E_w(f)$ in order to compare directly with the Fourier energy spectrum of the signal $E_f(f)$. To do this, we must convert from the wavelet a scale (which can be interpreted as a representative temporal, or spatial, period for physical data) to a characteristic frequency of the wavelet, e.g. the passband frequency or the central frequency. Using this passband frequency, the characteristic frequency associated with a wavelet of arbitrary a scale is given by

$$f = \frac{f_c}{a} \quad (5)$$

where f_c , the passband centre of the mother wavelet (i.e. $a=1$), becomes a scaling constant and f is the representative or characteristic frequency for the wavelet at arbitrary scale a . The wavelet-based power spectrum is then given by

$$P_w(f) = \frac{1}{\tau f_c C_g} \int_0^{\tau} |T(f, b)|^2 db \quad (6)$$

where τ is the temporal length of signal. The area under the $P_w(f)$ curve gives the total power in the signal.

B. The Study Data

This study is based on an 838 patient data set of ECG recordings of VF immediately prior to countershock. These measurements were grouped according to shock outcome as shown in table 1. Outcome was defined as ROSC (i.e. w_1) if a palpable pulse was present in the post-shock period (more information is given in reference [16]). The rest of the shocks correspond to No-ROSC (w_2 - w_5), including conversion to Electromechanical Disassociation (EMD) or Pulseless Electrical Activity (PEA), asystole, VF - where the VF starts after 5 seconds from the shock - and VF - where the VF starts within 5 seconds from the shock.

TABLE I
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Class	Shock Outcome	Number of Traces
w_1	ROSC	81
w_2	EMD/PEA	335
w_3	Asystole	93
w_4	VF starting > 5 seconds after shock	28
w_5	Non-reset shock – i.e. no conversion	301
Total		838

C. Data Preprocessing

The continuous wavelet transform was computed for each VF signal prior to countershock. The wavelet-based power spectrum was then computed from each of the resulting scalograms. Figures 1 and 2 show two typical ECG traces which include the pre-shock VF, the shock itself, and the post-shock outcomes. The outcomes are ROSC for figure 1 and Asystole for figure 2. Noticeable in both plots is the rich topography of the pre-shock scalogram. In this study we used features from the wavelet power spectra, $P_w(f)$, derived from the pre-shock scalogram to predict shock outcome. The wavelet power spectra corresponding to the pre-shock trace segments in figures 1 and 2 are shown in figure 3.

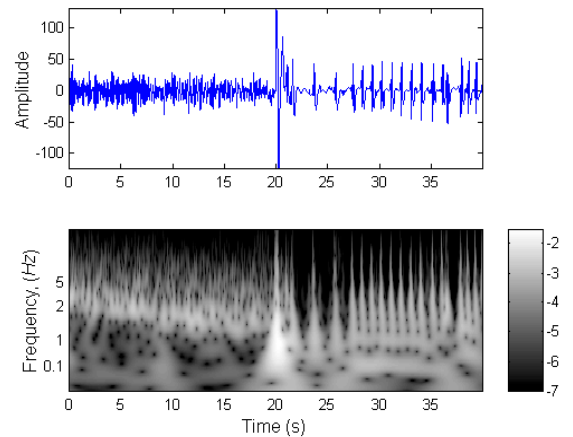


Fig. 1. Top: a segment of VF trace containing pre-shock VF and post-shock outcome w_1 (i.e. ROSC). Bottom: the corresponding scalogram.

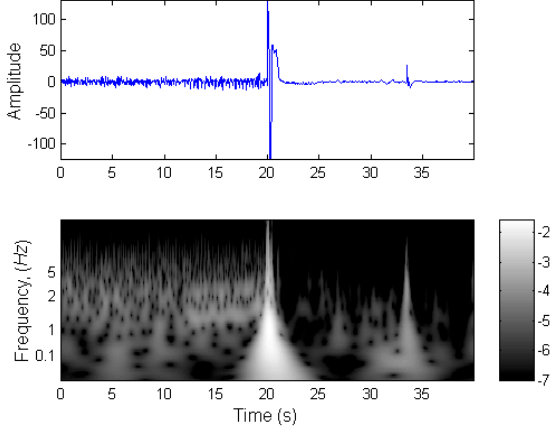


Fig. 2. Top: a segment of VF trace containing pre-shock VF and post-shock outcome w_3 (i.e. asystole). Bottom: the corresponding scalogram.

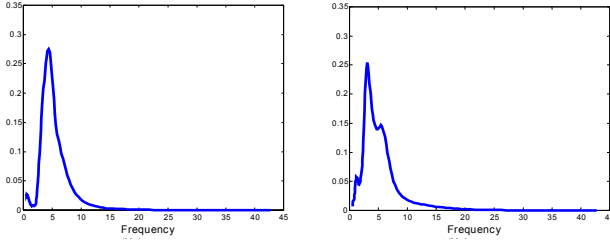


Fig. 3. Wavelet power spectra corresponding to the pre-shock trace in figure 1 (left) and the pre-shock trace in figure 2 (right).

A number of characterising features from the wavelet-based power spectral densities were then examined as potential markers for shock outcome prediction. These included: median frequency (FM) defined (in terms of a discretised power spectrum) as

$$FM = \frac{\sum_{f=0}^{\infty} f P_w(f)}{\sum_{f=0}^{\infty} P_w(f)} \quad (7)$$

and peak power frequency (PPF) defined as

$$PPF = \arg \max_f (P_w(f)) \quad (8)$$

D. Data Classification

As stated above, the five outcomes (w_i $i=1, \dots, 5$ shown in table 1) were further clustered into two groups: w_1 corresponding to ROSC and w_{2-5} corresponding to a No-ROSC outcome. The feature vector \mathbf{v} , derived from the spectral characteristics, was considered belonging to one of these 2 groups. In each case, the probability density functions of feature \mathbf{v} with respect to class w_j , $p(\mathbf{v}/w_j)$, were estimated as a discrete histogram. The *a posteriori* probability for each

class conditioned on the observation \mathbf{v} is calculated using Bayes rule defined as

$$P(w_j / \mathbf{v}) = \frac{P(w_j) p(\mathbf{v} / w_j)}{\sum_{i=1}^k P(w_i) p(\mathbf{v} / w_i)} \quad ; \quad j = 1, \dots, k \quad (9)$$

and $k=2$ corresponding to the ROSC and No-ROSC cases.

Using these probabilities we split the feature space \mathbf{V} into decision regions R_i , $i = \dots, k+1$. (The extra class represents the reject class.) This is done by assigning a cost function $C(w_i, w_j)$, which describes the loss suffered if class w_j is decided when the true class is in fact w_i .

Sensitivity and specificity are computed, where sensitivity is defined for the general case as

$$P_{sens}(w_i) = P(R_i | w_i) \quad (10)$$

and specificity is defined as

$$P_{spec}(w_i) = \frac{1}{1 - P(w_i)} \sum_{j, k \neq i} P(w_k) P(R_j | w_k) \quad (11)$$

The cost function is tuned iteratively to minimise the object function $J = [P_{sensa}(w_i) - P_{sens}(w_i)]^2$ so that the classifier meets the performance criterion defined by P_{sensa} .

III. RESULTS

Both the ROSC and No-ROSC data was partitioned equally into a training group and a test group. The characteristic features for the training group data were computed and the probability density functions of the feature vectors with respect to class w_j , $p(\mathbf{v}/w_j)$, were estimated. The sensitivity was specified for the recognition of ROSC outcome as $P_{sensa}(w_1)=95\%$. This was done for various bin sizes (in the partitioning of the scalogram information) and Gaussian kernel widths (in the reconstruction of the feature PDF's). The cost functions found for each case was then used to test the remaining data. As an example, the sensitivities and specificities corresponding to the test data are shown in figure 4 where the feature vector contains a single term: that of the median frequency FM . It can be seen in the figure that the sensitivities for the test set data are all close to the 95% attained for the training set. The specificities peak in value for a Gaussian kernel width of 2Hz (=six standard deviations) and 128 bins. This type of analysis was also carried out for other features and combination of features.

IV. DISCUSSION

In previous work [5-7] we showed that by employing continuous wavelet transforms, rather than representing

disorganised and unstructured electrical activity of the heart, the surface electrocardiogram recorded during ventricular fibrillation (VF) contains a rich underlying structure. In this paper we have detailed preliminary work which attempts to use parameters derived from wavelet-based power spectral densities of the pre-shock signal to predict shock outcome. The work is directly comparable with other groups who have attempted to classify shock outcomes from spectral characteristics of these signals derived from the Fourier methods [16,17,18].

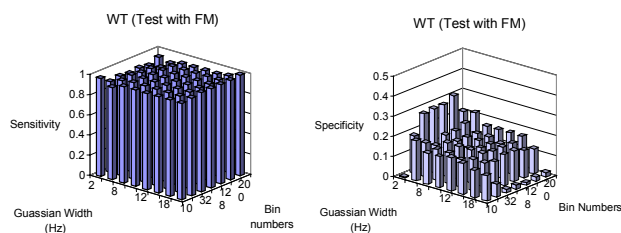


Fig. 4. Left: the test set results with the training set tuned to 95% sensitivity. Right: the corresponding specificity for the test set.

V. CONCLUSION

Although at an early stage, preliminary results from the work detailed here indicate that the predictive power of wavelet-based power spectral features is at least on a par with traditional Fourier-based and STFT-based spectral analyses. The method may be further enhanced by fine-tuning, which may include: the selection of an optimal wavelet, the use of a finer bin resolution to generate the PDF's, and the use of principle component analysis to better separate the feature data. It is, classification based on individual features within the pre-shock scalogram, however which promises to demonstrate the considerable strength of a wavelet-based analysis. This type of feature analysis cannot be achieved using STFT [5,6] due to its fixed window width. It is in this direction that the research is now focussed.

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